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Bidirectional Spatial–Temporal Network for Traffic Prediction with Multisource Data

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Abstract

Urban traffic congestion has an obvious spatial and temporal relationship and is relevant to real traffic conditions. Traffic speed is a significant parameter for reflecting congestion of road networks, which is feasible to predict. Traditional traffic forecasting methods have poor accuracy for complex urban road networks, and do not take into account weather and other multisource data. This paper proposes a convolutional neural network (CNN)-based bidirectional spatial–temporal network (CNN-BDSTN) using traffic speed and weather data by crawling electric map information. In CNN-BDSTN, the spatial dependence of traffic network is captured by CNN to compose the time-series input dataset. Bidirectional long short-term memory (LSTM) is introduced to train the convolutional time-series dataset. Compared with linear regression, autoregressive integrated moving average, extreme gradient boosting, LSTM, and CNN-LSTM, CNN-BDSTN presents its ability of spatial and temporal extension and achieves more accurately predicted results. In this case study, traffic speed data of 155 roads and weather information in Urumqi, Xinjiang, People's Republic of China, with 1-min interval for 5 months are tested by CNN-BDSTN. The experiment results show that the accuracy of CNN-BDSTN with input of weather information is better than the scenario of no weather information, and the average predicted error is less than 5%.

Traffic congestion has become an important factor affecting people's daily travel and the sustainable development of cities. In the past decade, researchers have proposed (*1*, *2*, *3*, *4*) various methods of traffic prediction to alleviate this kind of problem. Predicting important parameters of traffic flow, such as speed, is a feasible way to reflect the transmission of congestion. As high-resolution trajectory data, such as electronic navigation and positioning data, connected vehicles, and so forth, are available (*5*), dynamic network-level traffic prediction is practicable. Traditional traffic forecasting methods are mainly divided into two categories: one is based on mathematical models and statistical analysis; the other is based on big data and deep-learning algorithms. The former has many assumptions, ideal application scenarios, and poor prediction accuracy. With the development of big data and computational intelligence, the latter can predict future traffic more accurately based on historical data, save a lot of manpower and material resources, and fully excavate data to realize its application value. However, most of the existing methods are mainly applied to simple traffic networks or even road sections, and less traffic characteristics are considered. In fact, traffic flow has obvious spatial and temporal characteristics (*6*,*7*), and there are various factors affecting the variation of traffic volume and congestion transmission, such as severe weather conditions, traffic accidents, and so forth. It is very challenging to take into account so many factors for traffic network forecasting with big data.

As the data source becomes increasingly affluent and the relationship hidden behind the data is hard to depict with apparent formulation, deep learning tends to play

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an important role; it simulates the multilayer perception structure similar to information transmission among human brain neurons to recognize nonlinear data patterns. Especially with the advantages in image feature extraction and time-series recurrent learning, deep-learning models, such as convolutional neural network (CNN) and long short-term memory (LSTM), have shown excellent performance in traffic prediction with spatial and temporal information (*8*,*9*). This paper uses trajectory data and weather information to map traffic speed in traffic networks and form a series of traffic status images with weather labels. Then, both the spatial contiguous relationship of the whole road network and the temporal relationship of different traffic maps in time stamps can compose a complete dataset to realize accurate traffic prediction based on the advantages of deep learning. From a spatial view, the traffic speed in recent intervals of contiguous roads shares a strong spatial connection in traffic congestion propagation, which should be determined with spatial techniques. From a temporal view, adjacent intervals in the same road segment have an obvious time-series regulation in traffic congestion propagation, which should be solved by recurrent methods, such as LSTM and bidirectional long short-term memory (BiLSTM), for both forward and backward transmission of temporal congestion. To learn the hidden regulation behind the road network speed maps, this paper proposes a hybrid deep-learning model to extract the spatial characteristics of traffic roads and predict traffic time-series maps (*10*,*11*).

The rest of this paper is organized as follows.

1. Literature review of traffic flow forecasting methods is presented.
2. A new traffic forecasting model is proposed to consider spatial and temporal characteristics and external factors.
3. Multisource traffic data are introduced and preprocessed.
4. The proposed model and benchmarks are validated and compared with data from Urumqi, Xinjiang, People's Republic of China.

Literature Review

Over the past decades, scholars have conducted research on traffic flow forecasting. (*12*,*13*,*14*) The existing forecasting models are mainly divided into two categories: prediction based on mathematical models and prediction based on big data and deep learning.

Prediction Based on Mathematical Models

Mathematical models assume that the traffic flow data in the future will have the same characteristics as the historical traffic flow data, so the traffic flow, traffic speed, traffic density, and other traffic characteristics data can be processed by mathematical statistics to predict the traffic flow situation. This kind of model mainly includes historical average model, time-series model, Kalman filter model, and so on. Williams et al. (*15*) used an exponential smoothing algorithm to optimize the historical average model when predicting traffic flow of urban expressways. Levin and Tsao (*16*) used the Box–Jenkins time-series analysis method to predict the traffic flow of expressways and found that the autoregressive integrated moving average (ARIMA) [0,1,1] model was the most effective. In contrast, Kirchgassne and Wolters (*17*) discussed principles, algorithms, and applications of modern time-series analysis. Okutani and Stephanedes (*18*) first applied the Kalman filtering theory to dynamic prediction of short-term traffic flow in 1984. Van Lint (*19*) applied the Kalman filter model to online real-time prediction of traffic flow. Wang et al. (*20*) proposed a meta-analysis method to predict traffic accidents of connected vehicles and automated vehicles.

Prediction Based on Big Data and Deep Learning

Compared with the mathematical models, the learning-based models with big data do not rely on strict data deduction and clear physical equations, which have stronger adaptability to complex traffic networks. The main models are the support vector machine (SVM) and neural network (NN). SVM maps linear inseparable samples in a low-dimensional input space to a high-dimensional feature space by using non-linear mapping transformation (i.e., kernel method), so that the samples in the low-dimensional feature space can be separated in many cases in the high-dimensional feature space. Castro-Neto et al. (*21*) used an online SVR model to predict short-term traffic flow in typical and atypical environments. Jeong et al. (*22*) further developed the online SVR model into supervised online weighted SVM regression.

NN, on the other hand, is widely used in almost all fields, including traffic forecasting. NN can simulate complex non-linear problems and shows significant performance in processing multidimensional data. Smith and Demetsky (*23*) used back propagation NN to predict earlier short-term traffic flow. Hu et al. (*24*) input historical traffic flow data into back propagation NN after difference, and then predict short-term traffic flow in the next moment. Khotanzad and Sadek (*25*) applied multilayer perceptron and fuzzy NN to high-speed network traffic prediction; their results indicated that NN performed better than the autoregressive model (*25*). Tan and Wang (*26*) achieved 85% accuracy of traffic congestion prediction with an auto-encoder network for an unlabeled dataset and softmax regression for a labeled dataset using pattern recognition.

In recent years, the success of deep learning in the field of computer vision has prompted many scholars to apply it to traffic prediction. For example, Ma et al. (*27*) used CNN to predict traffic speed with slots of traffic speed pictures. CNN could effectively determine the spatial relationship between links of the speed pictures. However, the interchange of roads was treated arbitrarily with average speed at an intersection and different directions of roads were not considered. Other studies used the LSTM model to predict traffic flow, showing the characteristics of traffic congestion propagation and time dependence, which was better than SVM (*28*, *29*) in prediction accuracy but lacked sufficient spatial correlation to represent the entire road network. To make up for the shortcomings of the above-mentioned two models, some scholars combined the two models. Wu et al. (*30*) established a short-term traffic flow forecasting method based on CNN and LSTMS for main roads. Yu et al. (*31*) used the DCNN (deep convolutional neural network)-LSTM model to forecast traffic flow in large-scale road networks. Yao et al. (*32*) proposed a deep multi-view spatial–temporal network framework to model both spatial and temporal relationships.

The above-mentioned models only consider the characteristics of the traffic itself, without considering the characteristics of the external impact on traffic. In fact, these factors have a great impact on traffic. For example, bad weather conditions, such as rain and snow, seriously affect driving and the average speed of vehicles on the road, resulting in a drop in traffic capacity and widespread congestion. Considering the influence of weather conditions as labels on speed transmission, this paper proposes a convolutional neural network-based bidirectional spatial–temporal network (CNN-BDSTN) to train and test spatio-temporal speed maps. The CNN model is used to extract in-depth spatial characteristics of the traffic network and its output results and weather eigenvalues are fed into BiLSTM to learn the temporal characteristics of traffic congestion evolution. This model not only considers the temporal and spatial characteristics of traffic but also takes into account the influence of weather factors, which greatly increases the practicability and robustness of the model.

Bidirectional Spatial–Temporal Network Model

This paper presents an in-depth introduction to CNN-BDSTN with a two-dimensional CNN and BiLSTM model.

Spatial Characteristic Analysis

Roads of traffic network are closely related to each other, as the upstream determines the congestion of downstream by inflow and the downstream influences the congestion of upstream by spillover. Traffic congestion is transmitted through the whole network. CNNs can capture spatial features efficiently.

In this paper, the actual speed of each section of traffic network is mapped into the road network and divided into different regions. Each region represents the same pixels, and the information contained in each pixel is the input data of the CNN model. As shown in Figure 1, each slot of traffic speed maps is grayed for building up normalized image information, and the speed values are scaled down to [0,1]. An $S*S$ convolution kernel is used to convolute the image. The size of S determines the range of the whole space. Padding is not used here because the value information of urban road network boundary is not very high. Consequently, a filter is used to scan each image and extract the features of each image.

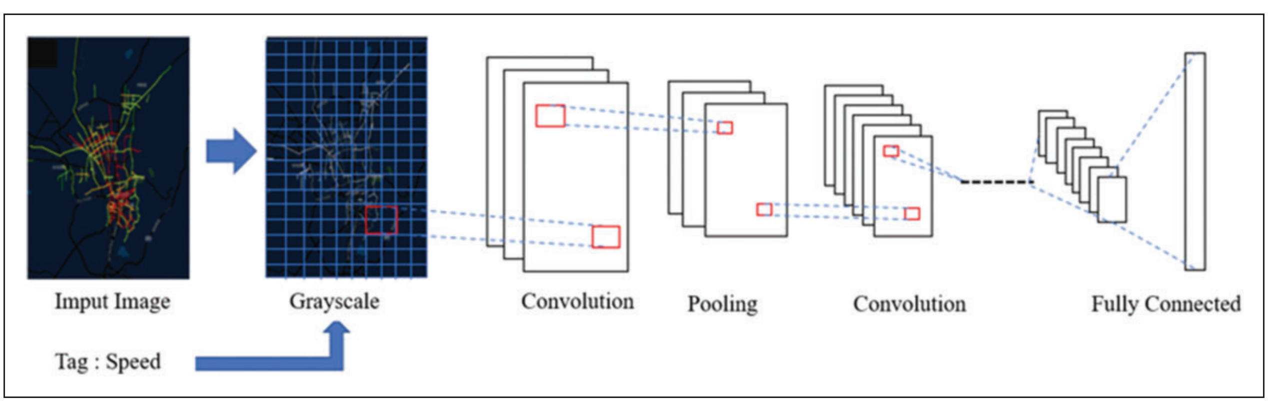

Figure 1. Steps of the CNN on extracting speed feature.
Note: CNN = convolutional neural network.

The target region of image in interval t is represented by i. Using the $S*S$ convolution kernel as a filter $Y_{i,t} \in \mathbb{R}^{S*S*1}$, the local CNN takes $Y_{i,t}$ as input $Y_{i,t}^{(0)}$, and the formulation of each convolutional layer k is expressed as:

$$Y_{i,t}^{(k)} = \mathrm{ReLU}\left(W^{k} * Y_{i,t}^{(k-1)} + b^{(k)}\right) \tag{1}$$

where $W^{(k)}$ and $b^{(k)}$ denote weight and bias, respectively, * denotes the convolution operation, and ReLU is a nonlinear activation function. After the convolution operation, the most significant eigenvalues are extracted by the maximum pooling method to reduce the parameters of the model. Finally, after several convolution pooling operations, the fully connected layer is used to stitch the results together to obtain the features of the whole picture and reduce the impact of feature locations of the roads.

Temporal Characteristic Analysis

The temporal characteristic of traffic flow is not static but varies with time. Therefore, traffic flow has obvious temporal characteristics, and the propagation of traffic congestion can be seen clearly through time series, as shown in Figure 2. Urumqi, as one of the cities whose road network is not very complex and easy to observe in Xinjiang, China, is selected, where two stochastically selected contiguous roads, Guangming Road and Xinhua Road, clearly show the spread of congestion.

At present, the LSTM method is basically used for deep learning with sequence properties. This model can solve the problems of gradient explosion and disappearance of the traditional recurrent neural network (RNN). By introducing the "forgetting gate" mechanism, the LSTM model forgets part of the previous information and inputs more valuable information into the layer model, which successfully avoids the above-mentioned problems. However, LSTM is transformed from RNN. It only studies and trains in one direction, ignoring the future road condition. From the view of traffic temporal transmission, the importance of both temporal directions is equal, as the similar speed distribution of road network is very likely from different speed time-series. For instance, the process of congestion formation and dissipation produces many pairs of similar speed conditions, which urges the consideration of both sides of the recurrent speed time-series. The role of direction is very important, and the one-way LSTM model cannot capture such features. To solve this problem, the BiLSTM model is introduced in this paper, which combines the forward LSTM model with the backward LSTM model. In this way, the eigenvalues before and after the prediction can be more accurately captured, leading to the prediction results in time series being more accurate. BiLSTM is a combination of two single LSTMs, so the advantages of the LSTM model are described in detail here and a schematic diagram of the BiLSTM model is given (Figure 3).

On the basis of the RNN model, the LSTM model introduces a gate mechanism, which controls the amount of information passing through. The model contains three gates: "forgetting gate," "input gate," and "output gate." The traditional LSTM model is as follows:

$$\text{Forgetting gate}: f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{2}$$

$$\text{Input gate}: \begin{aligned} i_t &= \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \tilde{C}_t &= \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\ C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \end{aligned} \tag{3}$$

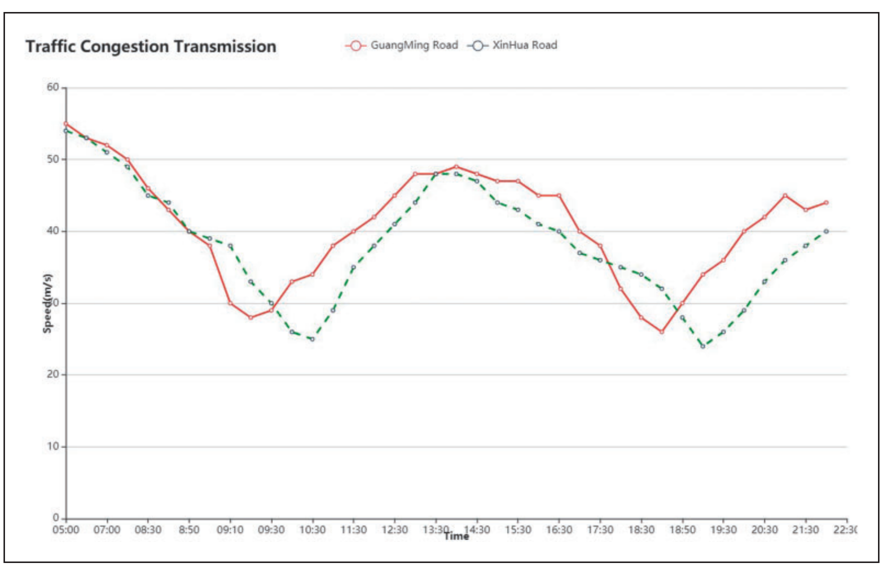

Figure 2. Traffic congestion transmission.

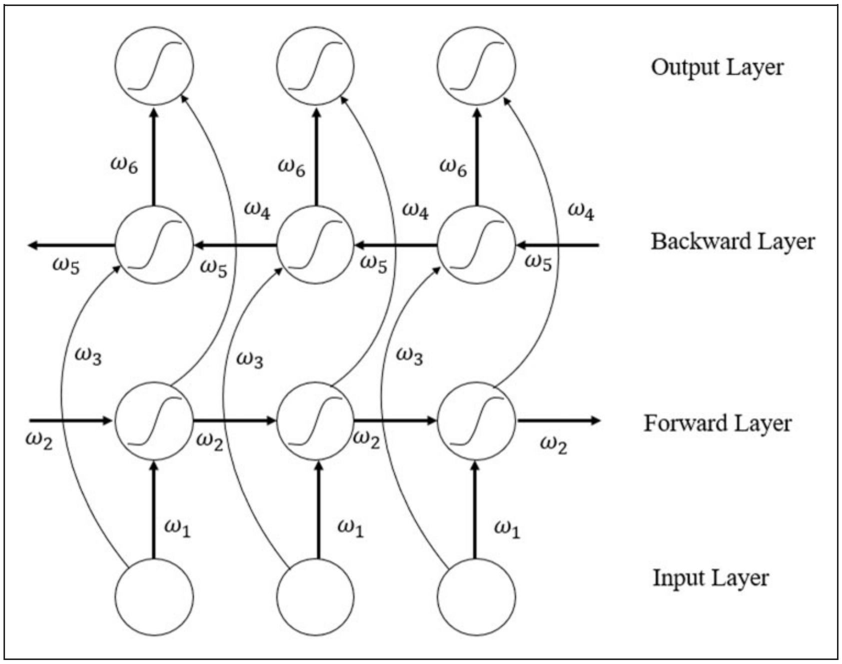

Figure 3. Structure of the BiLSTM model.
Note: BiLSTM = bidirectional long short-term memory.

$$\text{Output gate}: \begin{array}{l} o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \\ h_t = o_t * \tanh(C_t) \end{array} \quad (4)$$

The LSTM model is composed of t time vector x_t, cell state C_t, temporary cell state $\tilde{C}_t$, hidden layer state h_t, forget gate f_t, memory gate i_t, and output gate o_t. The above-mentioned LSTM model is applied twice, for forward propagation and backward propagation, which forms the BiLSTM model. As in Equation 5, h_t^L and h_t^R denote forward propagation and back propagation, respectively. As shown in Figure 3, ω is the weight of the model.

$$h_t = \left[h_t^L, h_t^R\right] \quad (5)$$

External Factors

The traffic system is a complex system that is easily disturbed by external factors, such as emergencies, weather, and so forth. In the same road network, bad external environment seriously restricts people's travel and affects the speed of traffic operation. In Figure 4, under the influence of heavy rain or other weather conditions in Urumqi, traffic speed shows an obvious drop because of low visibility, compared with that on sunny days. Different weather factors have different effects on traffic flow characteristics. When the speed of traffic flow is significantly reduced, congestion is more likely to occur.

Considering different weather conditions, the weather dataset is divided into snowy, foggy, rainy, cloudy, and sunny days, with the assigned values of 0.9, 0.7, 0.6, 0.3, and 0.2, respectively (*26*). Thus, it can be input into the CNN-BDSTN model with traffic speed as a multisource dataset. Therefore, the input of the BiLSTM model x_t will become $x_t = [x_t, e_t]$, where e_t means external features.

CNN-BDSTN Model

Based on the sub-model mentioned above from both spatial and temporal views, CNN-BDSTN is built up by combining each sub-model and realizing the traffic flow prediction model with multisource dataset. First, the speed dataset is drawn into maps. Then, each map is continuously input and output from the CNN model. Afterwards, the weather feature vectors and CNN output results are joined together as the multisource input of the BiLSTM model. Finally, the output of the BiLSTM model is treated as the complete connection layer. In Figure 5, the framework of the proposed CNN-BDSTN model considers the effects of time, space, and weather to predict the future speed network.

Experiment

Data Description

The main data of this study are obtained through web crawler technology and Gaode Application Programming Interface (API). First, the traffic

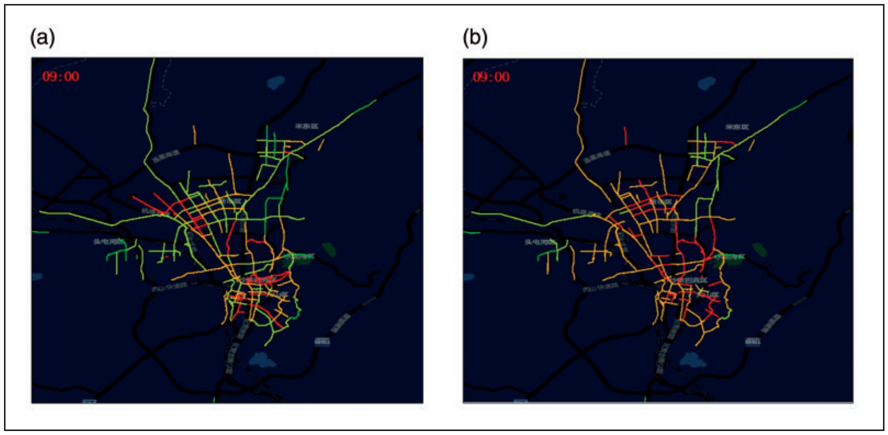

Figure 4. Congestion during different weather conditions: (*a*) sunny weather and (*b*) rainy weather.

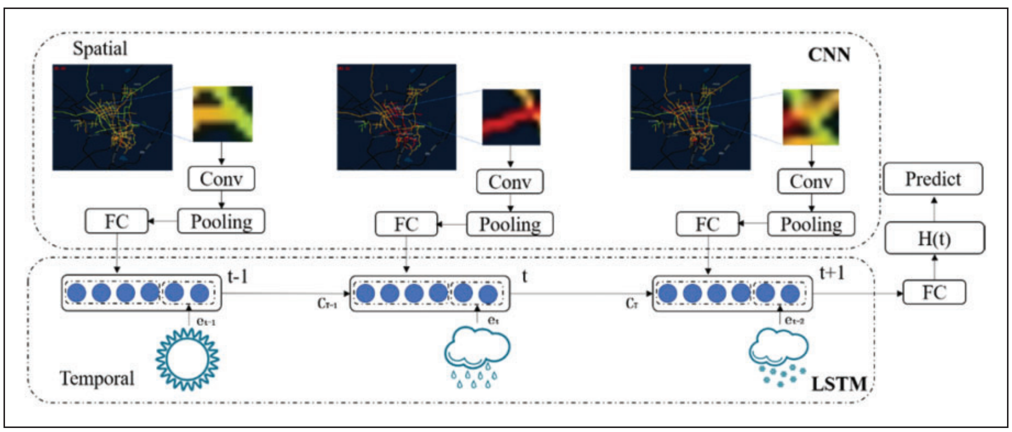

Figure 5. Framework of the CNN-BDSTN model.
Note: FC = fully connected; Conv = convolution; CNN-BDSTN = convolutional neural network-based bidirectional spatial–temporal network; LSTM = long short-term memory.

network information of Urumqi is captured, with a total of 155 sections. Second, the traffic speed data of Urumqi from January 1, 2019 to May 31, 2019 (151 days) are crawled 24 h a day with a time interval of 1 min. Daily data size is 1,440 × 155. Relevant positioning information can match speed data to the road network accurately to generate traffic speed maps. Finally, the all-day weather data in Urumqi are matched to the traffic speed maps.

Considering the calculating efficiency and the efficient variation gradient of time series, the time intervals of the input data are aggregated to 10 min. Consequently, 144 speed maps and weather status are recorded every day. To verify the accuracy of the model, the dataset is divided into the training set and the test set. The training set helps to train the model, whereas the test set tests the accuracy of the trained model. Therefore, 80% of the dataset is used as training data and 20% as test data.

Implementation

The parameter setting of the model is very important for accuracy. All the convolution kernels of the CNN are set to 3 × 3 in size. The learning rate is set to 0.001, the decay parameter is set to 0.9, and the batch size is set to 256. The loss function is mean square error. A batch normalization layer is used to overcome internal covariate shift. At the same time, to prevent overfitting, dropout is set as 0.2 to improve the generalization ability of the network. All the parameters in the paper are selected through numerous experimental data.

Evaluation Indicators

Here, two evaluation indicators are used to evaluate the prediction accuracy of different models, namely, mean average percentage error (MAPE) and rooted mean square error (RMSE). Other models to be compared include the CNN-LSTM model, the LSTM model, the extreme gradient boosting (XGBoost) model, the ARIMA model, and the linear regression (LR) model.

$$MAPE = \frac{1}{\zeta}\sum_{i=1}^{\zeta}\frac{|\hat{y}_t^i - y_t^i|}{y_t^i} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{\zeta}\sum_{i=1}^{\zeta}\left(\hat{y}_t^i - y_t^i\right)^2} \tag{5}$$

where $\hat{y}_t^i$ and y_t^i denote, respectively, the prediction speed and real speed of link i at time t; and ζ is total number of simples, where ζ = number of links × time.

Performance Comparison

With reference to the requirement of traffic management and guidance, various terms of prediction are compared as important properties. For example, people who are in a hurry can choose the best travel route based on recent short-term congestion of the road network; people who plan to travel an hour later can choose the appropriate route according to middle-term road conditions; and people who decide to travel tomorrow may search the prediction results the next day. According to middle-term and long-term predictions provided by Gaode in its platform, the speed of the targeted network will be predicted for every hour with the evolution of detected speed for every minute. However, the predicted speed of the targeted network is almost constant, even in peak hours, which is convinced to lose effectiveness. Therefore, here, the short-term (10 min), medium-term (1 h), and long-term (the next day at the same time) predicted results are compared.

Based on the above-mentioned results (Table 1), it is not difficult to find that the CNN-BDSTN method proposed in this paper achieves the best results on MAPE and RMSE. Further analysis shows that the performance of traditional traffic prediction methods (LR and ARIMA) is not good, especially with the extension of time. The robustness of the model decreases rapidly, with MAPE and RMSE increasing by 400% and 177%, respectively. This is because they predict with fixed simple average and equation on historical data with weak generalization ability. The regression-based method (XGBoost) performs better than traditional methods, with abundant tree selections and multiple mechanisms to avoid overfitting. However, large computation of speed prediction of the road network cuts down its efficiency and accuracy. With respect to deep-learning methods, the results of LSTM and CNN-LSTM are much better than those of other models, with CNN and LSTM working on spatial and temporal fields, respectively. MAPE and RMSE increase by nearly 50%. As LSTM ignores the spatial connection, CNN-LSTM performs slightly better than LSTM. Especially in the middle-term and long-term forecasting, this kind of superiority is noteworthy as MAPE and RMSE decrease by 52.8% and 30.7%, respectively, in the long term. By considering both sides of temporal information transmission as a complete course with BiLSTM, CNN-BDSTN makes the most accurate and stable prediction under different terms of predictions, with MAPE within 0.2 and RMSE around 20.

Advantage of Spatial Convolution

In the spatial network, either upstream and downstream connections or intersections and ramp-connected roads have a close congestion relationship, which affects the accuracy of prediction a lot. CNN is applied to convolute the contiguous roads together to enhance accuracy. To test the function of CNN, CNN-BDSTN with non-weather (CNN-BDSTN-NW) and BiLSTM are compared (Figure 6). The difference between CNN-BDSTN-NW and BiLSTM is whether there exists a

Table 1 Comparison among Different Methods

	Short-term (10 min)		Middle-term (60 min)		Long-term (next day)	
Method	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE
LR	0.25	38.12	0.45	51.32	1.01	67.55
ARIMA	0.22	32.68	0.38	47.12	0.75	58.11
XGBoost	0.21	30.89	0.35	42.22	0.66	50.34
LSTM	0.19	23.15	0.32	38.58	0.53	40.35
CNN-LSTM	0.18	21.47	0.22	24.15	0.25	27.95
CNN-BDSTN	0.15	19.97	0.16	19.21	0.19	21.12

Note: MAPE = mean average percentage error; RMSE = rooted mean square error; LR = linear regression; ARIMA = autoregressive integrated moving average; XGBoost = extreme gradient boosting; LSTM = long short-term memory; CNN-LSTM = convolutional neural network-based long short-term memory; CNN-BDSTN = convolutional neural network-based bidirectional spatial–temporal network.

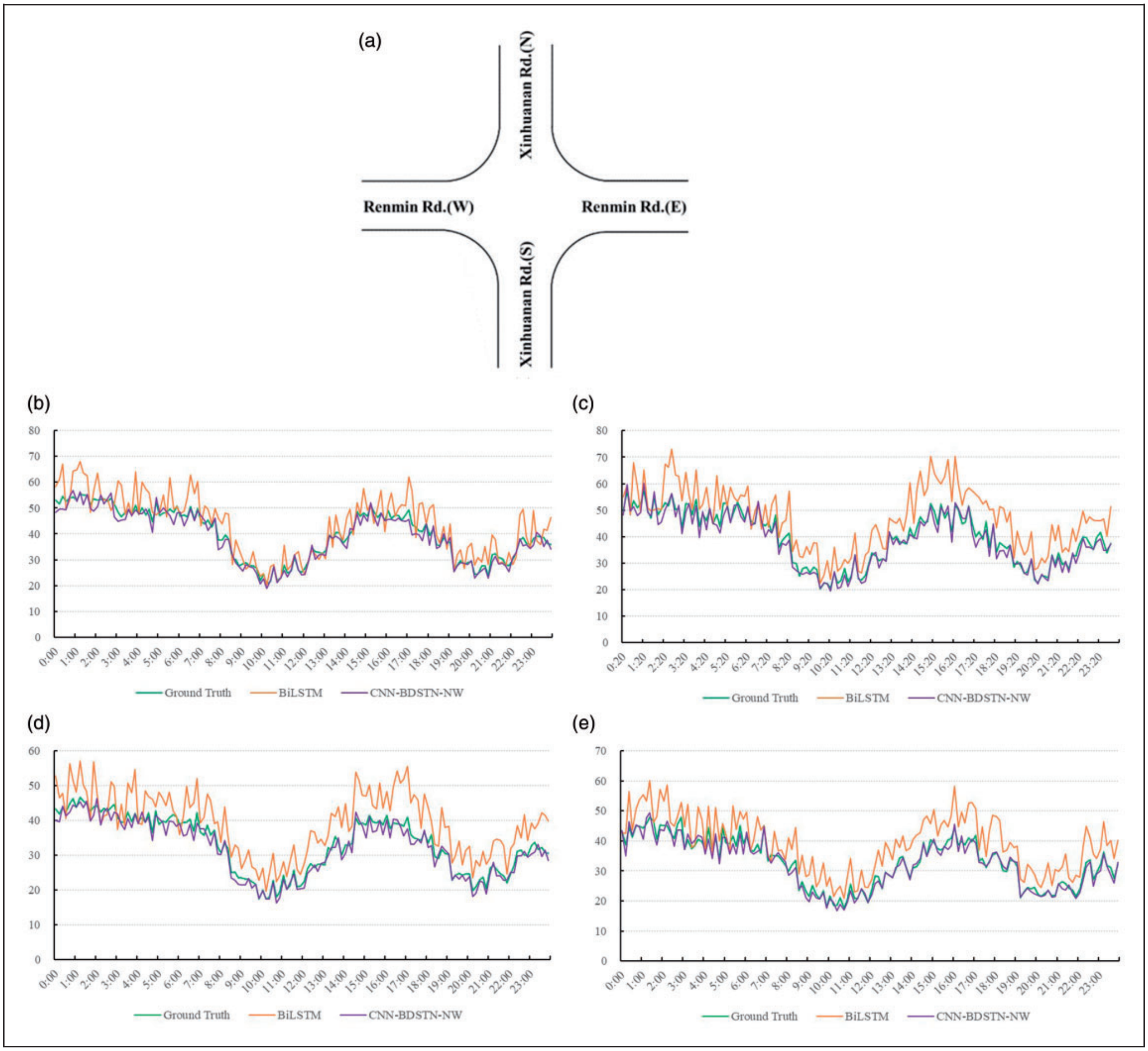

Figure 6. Sample of CNN spatial performance between contiguous roads (Renmin Rd. and Xinhuanan Rd.) by BiLSTM and CNN-BDSTN-NW. (*a*) Layout of sample of Urumqi (Renmin Rd. [East–West] and Xinhuanan Rd. [North–South]), (*b*) Renmin Rd. (W), (*c*) Renmin Rd. (E), (*d*) Xinhuanan Rd. (S), and (*e*) Xinhuanan Rd. (N).
Note: CNN = convolutional neural network; BiLSTM = bidirectional long short-term memory; CNN-BDSTN-NW = convolutional neural network-based bidirectional spatial–temporal network with non-weather.

CNN model. There are four roads: Renmin Rd. (W), Renmin Rd. (E), Xinhuanan Rd. (S) and Xinhuanan Rd. (N). From Figure 6, (*b*)–(*e*), CNN-BiLSTM-NW outperforms BiLSTM with high accuracy around the ground truth.

Advantage of a Bidirectional Model

As the process of congestion formation and dissipation produces many pairs of similar speed conditions, both temporal transmission sides of roads in the network maps should be considered. As the LSTM model only considers the direction of backward propagation, the BiLSTM model is introduced to consider both forward and backward transmission of time series for more accurate and robust prediction.

Different epochs are set for the model, and the accuracy of propagation between CNN-LSTM and CNN-BDSTN-NW is compared through the roads of maps. The difference between the two control methods is whether unidirectional or bidirectional temporal training is introduced. The accuracy of the CNN-LSTM model is below 80%, whereas that of the CNN-BDSTN-NW model is about 90%, which is approximately 15% higher than that of the CNN-LSTM model. As the training epoch increases, CNN-BDSTN shows 7% improvement (1% more than CNN-LSTM) and reaches 95% accuracy (Table 2).

Table 2 Accuracy of the CNN-BDSTN Model with Different Epochs at Intersections

Epochs	CNN-LSTM (%)	CNN-BDSTN-NW (%)
50	72	88
100	75	93
150	78	94
200	78	95

Note: CNN-LSTM = convolutional neural network-based long short-term memory; CNN-BDSTN = convolutional neural network-based bidirectional spatial–temporal network; CNN-BDSTN-NW = CNN-BDSTN with non-weather.

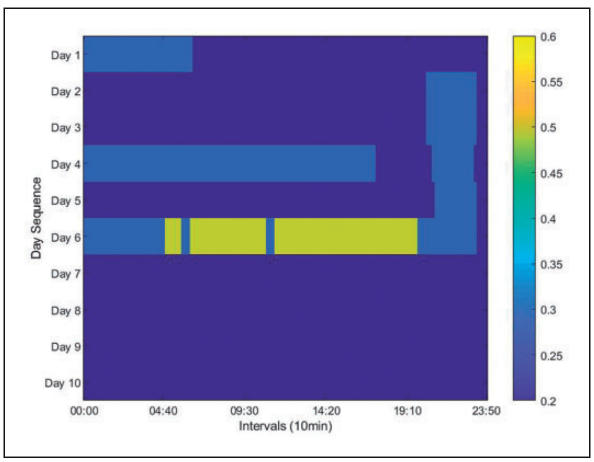

Figure 7. Weather information of selected days.

Advantage of Considering Weather

The above-discussed research has shown that the CNN-BDSTN-NW model has a high accuracy for traffic prediction. In practice, the accuracy of the model is highly influenced by external factors, such as weather conditions. In experiments, 10 days of 13 roads were selected from the test set to show the efficiency of considering weather factors (Figure 7), with obvious rainy weather on the sixth day. The predicted speeds under weather conditions (CNN-BDSTN) and non-weather conditions (CNN-BDSTN-NW) are compared with CNN-LSTM. In Figures 8 and 9, after abundant training of historical dataset, MAPE and RMSE of CNN-BDSTN show better prediction on the rainy sixth day because weather information is incorporated in the model as an external feature. It is noticeable that rainy weather with high influence on traffic speed greatly affects the accuracy of prediction. The predictions of different periods of day are also compared in Figures 10 and 11. Note that during evening hours before 8:00 a.m., the prediction is more steady because the variation in that period is really less. CNN-BDSTN-NW and CNN-BDSTN show stable prediction compared with CNN-LSTM with bidirectional propagation in most hours, especially during peak hours between 10:00 a.m. to 8:00 p.m. (Figure 11). This is because people of Urumqi have a 2-h time difference with Beijing. Between CNN-BDSTN and CNN-BDSTN-NW, CNN-BDSTN performs better than non-weather information from 7:00 a.m. to midnight and from 6:00 p.m. to 11:00 p.m. because the variation of weather is concentrated on this period of the first, fourth, and sixth day (see Figure 7). Therefore, it is significant to consider the weather for traffic prediction.

To further illustrate the importance of considering external conditions in the model, MAPE and RMSE are calculated under different weather conditions for 13

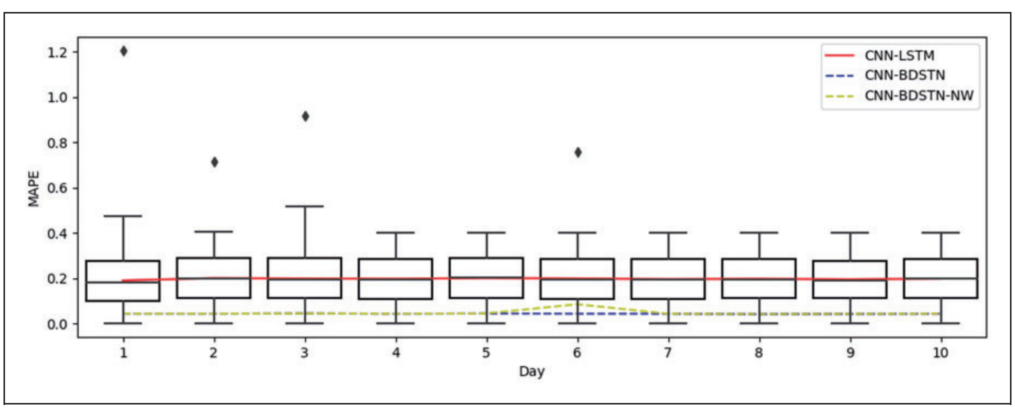

Figure 8. Weather and non-weather MAPE comparison on different days.
Note: MAPE = mean average percentage error; CNN-LSTM = convolutional neural network-based long short-term memory; CNN-BDSTN = convolutional neural network-based bidirectional spatial–temporal network; CNN-BDSTN-NW = CNN-BDSTN with non-weather.

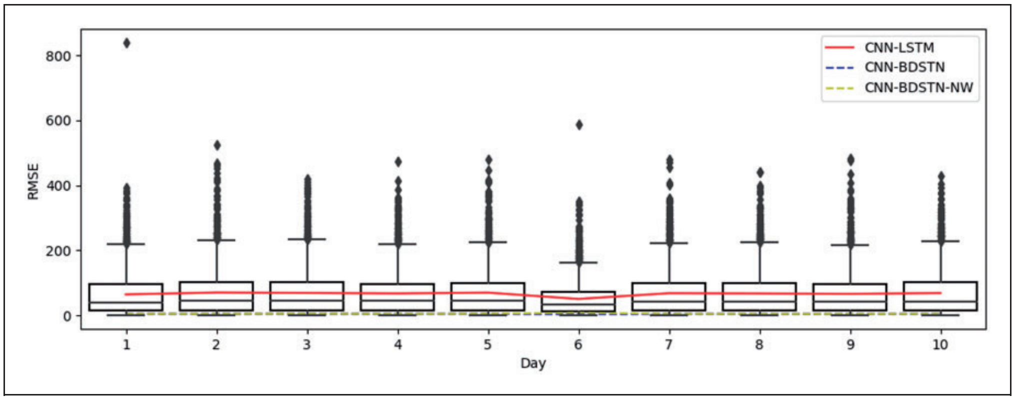

Figure 9. Weather and non-weather RMSE comparison on different days.
Note: RMSE = rooted mean square error; CNN-LSTM = convolutional neural network-based long short-term memory; CNNBDSTN = convolutional neural network-based bidirectional spatial–temporal network; CNN-BDSTN-NW = CNN-BDSTN with nonweather.

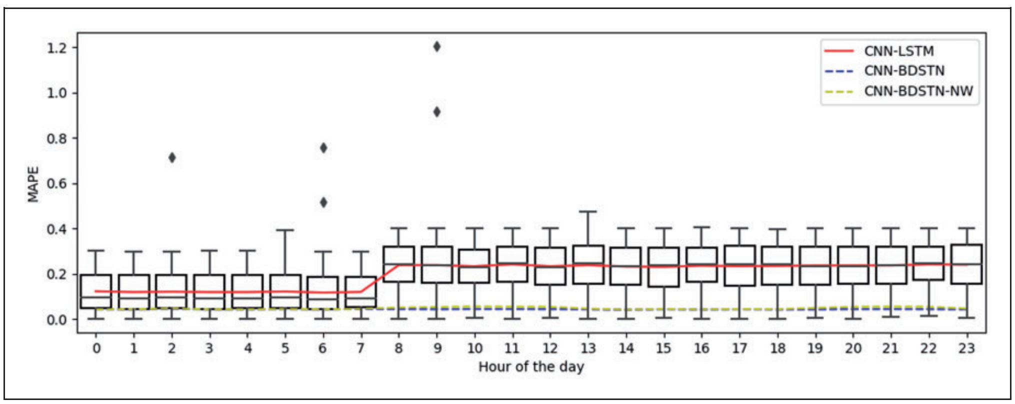

Figure 10. Weather and non-weather MAPE comparison at different periods of the day.
Note: MAPE = mean average percentage error; CNN-LSTM = convolutional neural network-based long short-term memory; CNNBDSTN = convolutional neural network-based bidirectional spatial–temporal network; CNN-BDSTN-NW = CNN-BDSTN with nonweather.

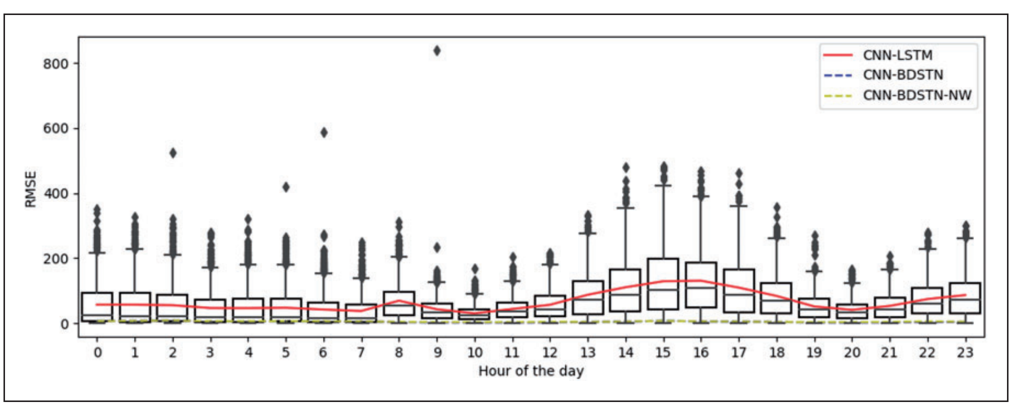

Figure 11. Weather and non-weather RMSE comparison at different periods of the day.
Note: RMSE = rooted mean square error; CNN-LSTM = convolutional neural network-based long short-term memory; CNNBDSTN = convolutional neural network-based bidirectional spatial–temporal network; CNN-BDSTN-NW = CNN-BDSTN with nonweather.

Table 3. Comparison of Different Roads with or without Weather

	CNN-BDSTN with weather		CNN-BDSTN-NW without weather	
Road	MAPE (%)	RMSE	MAPE (%)	RMSE
Guangming	4.30	14.92	8.73	29.50
Xinhuabei	3.79	10.30	13.56	15.88
Jiefangnan	6.40	18.32	8.28	27.56
Jiefangbei	5.90	14.07	15.06	25.79
Renmin	5.49	20.27	12.93	18.22
Minzhu	2.20	10.18	12.30	16.86
Xinhuanan	2.24	23.18	11.77	20.40
Longquan	4.16	19.16	8.55	15.36
Tuanjie	4.14	13.62	12.10	20.04
Hongdhan	5.18	10.65	10.54	25.17
Qingnian	6.08	17.02	10.36	25.11
Youhaonan	2.00	22.84	7.99	17.17
Yangzijian	4.00	16.91	7.51	25.43

Note: MAPE = mean average percentage error; RMSE = rooted mean square error; CNN-BDSTN = convolutional neural network-based bidirectional spatial–temporal network; CNN-BDSTN-NW = CNN-BDSTN with non-weather.

roads in the city center (Table 3). MAPE of prediction is most below 5% of CNN-BDSTN. On the contrary, results of CNN-BDSTN-NW are mostly higher than 10%. Moreover, the RMSE fluctuation range of the two methods is larger than that of MAPE, because of the obvious change of speed in different periods.

Conclusion and Discussion

With the rapid development of trajectory sampled data, traffic congestion can be predicted by measuring the variation of speed of the road network with consideration of weather influence. This paper proposed a CNN-BDSTN model with weather information based on CNN and BiLSTM deep-learning sub-models, for capturing the time and space characteristics of traffic flow, respectively. Compared with traditional methods, in the regression methods and deep-learning methods, the proposed CNN-BDSTN performed best with the evaluation indexes in different terms of prediction. The model also showed good potential for improvement through training with more epochs. The degree of improvement of prediction accuracy of weather influence, spatial convolution, and bidirectional propagation of time series was tested to show the efficiency of the proposed CNN-BDSTN model.

At present, the CNN-BDSTN model only introduces weather factors, but there are many other factors affecting traffic in real life. However, the proposed model has shown the plasticity of adding external factors, which also provides a good basis for further research. Thus, with sufficient multisource data, the prediction mechanism and accuracy can be revised remarkably.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: W. Ma and K. Han; algorithm implementation and experimental design: T. Sun; data collection: C. Yang; data contribution and analysis: F. Zhang; draft manuscript preparation: T. Sun and W. Ma. All authors reviewed the results and approved the final version of the manuscript.

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